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EEG STABILITY ANALYSIS: SLEEP RECORDS[1]

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Footnotes to Title Page

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INTRODUCTION

In recent years, automatic analysis of the electroencephalogram has become more and more complex (2) and yet farther from actual usefulness to the clinician. This is not surprising in the light of rapidly increasing sophistication in the biological use of computers. At the same time, this increasing sophistication presents both a problem and an opportunity. The difficulty arises from the practical problem raised for the clinician who has not the time to become a programmer or mathematician, nor usually the appropriate computer facilities at his disposal. However, the inherent nature of these computing techniques has the potential to overcome this difficulty. The opportunity would appear to lie in the utilization of large, general-purpose digital computers, not for routine analysis, but rather in a search for the most fruitful types of analysis or the most significant parameters to quantify EEG patterns. If, for example, it were possible to define the basic parameters necessary to appropriate analysis of the EEG, then it should be possible to design special-purpose computers capable of analysing such parameters. This would not relieve the clinician of his responsibilities in the integration of other clinical criteria with the EEG information, but it would provide more consistent data on which to base his judgement. The present paper is a first step in this direction, utilizing the UCLA Health Sciences computer[2] (IBM 7094) and the UCLA Space Biology Laboratory Spectral Analysis programs as the basis for searching for the pertinent parameters of the EEG. (2)We wish to express our thanks for the services provided by this facility operated under NIH Grant #USPHS FR3.

The analysis of time-dependent processes in terms of their spectral properties has long been a favorite scientific tool, in EEG and elsewhere. Its power derives from the property that the Fourier coefficients for linear (Gaussian) systems are independent even when the data is highly autocorrelated in the time domain. Thus, complex waves can be analyzed into component parts suggestive of changing generative processes. These are components by frequency and constitute an auto-spectrum.

Cross-spectra and transfer function analysis of the EEG are generally more useful tools, in our present state of knowledge, since they permit elucidation of functions (such as transmission) which can be more satisfactorily modeled at this time than the generative processes accessible through auto-spectral analysis. The pioneering work of D. O. Walter (7) has offered a tantalizing glimpse of new insights into cerebral function and information processing which will undoubtedly develop with wider application of these methods.

In an earlier paper (6), in which spectral analysis was used, certain problems arose in the interpretation. For example, the auto-spectra were quite similar for states of sleep rather easily differentiated by visual examination of the EEG. While it was possible to discern subtle difference, the spectra essentially showed that even though high frequency activity existed, there was an absence of a readily definable narrow band in these high frequencies; that is, the activity was widely dispersed in the higher ranges. For example, in a lead from the reticular formation one can see some slow activity but to the eye the predominant activity looks rapid (Fig. 1B). However, the spectra demonstrate clearly that only the low frequency activity is sufficiently ordered to have focalized power, while the higher frequencies, although obviously present, are dispersed over a wide range with little focalized power (Fig. 1A). While this interesting observation holds some promise for future understanding of cerebral activity, it does not seem to be what the electroencephalographer is using for interpretation in any direct sense.

Added to these difficulties are several other defects of spectral analysis from the point of view of the clinician rather than the researcher: at the present time, the spectra is expensive to compute; it does not achieve a sufficient degree of data reduction; and it does not adequately describe the shape of wave processes. We have attempted to circumvent some of these defects by deriving parameters suggestive of Gestalt perceptions of patterns in a wave process.

The electroencephalographer as a human computer makes certain decisions about an EEG record as he reviews it. He usually describes his findings in terms of frequency and/or amplitude which are obviously important, but also incomplete; it would seem as though other factors are also playing a significant role in the decisions being made. For example, why does the clinician respond to a burst of sharp theta as being within the limits of normality one time and significant of abnormality at another? It would be our contention that the electroencephalographer is responding to at least two factors (possibly more) that he normally does not describe (or combines under the term "synchrony"). One of these factors could be the clinical experience that this type of theta shows in this area with a particular clinical syndrome. While this type of consideration is of great importance, it involves many problems, for example language coding, and will not be dealt with in this paper. Another possible factor can be that of the degree of stability of the record, either in terms of the overall record or the specific part of the record in which this hypothetical theta appears. The latter factors are amenable to computer analysis. Since the electroencephalographer in viewing a record tends to impute an order to the data whether it exists or not; one may consider accepting the spectral data as the basis for calculating certain indices of orderliness. We have chosen two such indices, the dispersion or bandwidth of each spectrum, and the time spread or duration of each wave trace. They provide, when considered together, a useful characterization of the stability of a record, a measure of its orderliness.

STABILITY

The concept of stability is related to the idea of organization or non-randomness. For example, a sine wave is considered highly stable while white noise may be called highly unstable. There are two indications of this stability in a sinesoid - - the peak to peak amplitude stability.and frequency stability. A measure of frequency stability is the spread of the spectrum or the equivalent noise bandwidth (B) which will be narrow for highly stable functions, such as a sinesoid. The corresponding measure of amplitude stability is the spread of power in the time domain, or the duration, (τ). There are many alternative definitions (5) to those expressed here; the choice was based on the ease of adding the computation to an existing spectral analysis program, and the relative ease of developing a sampling theory for the chosen statistics.

The product of bandwidth and duration is known as the uncertainty, a quantity which crops up in a wide range of disciplines. In statistical communications theory the concept appears in the number of independent samples necessary to define a record. We may characterize the stability of phenomena according to the distribution in the field of uncertainty. Hence the plot of B versus τ as a function of time will be defined as the stability diagram of a process.

METHOD

1. Mathematical Definition

The underlying mathematical theory is not necessary for the usage or general understanding of the concepts of bandwidth and duration. A general theory has been established by Zakai (9) who defines a general class of bandwidth-duration measures. The definitions used in our system were chosen from those available in Zakai's classification.

Given a sample, $X(t)$, $0 \le t \le T$, from a random process with a sample spectral density $S(f)$, the sample bandwidth, B, is defined as:

$$B = \frac{\int_0^\infty S(f)df}{\max\,[S(f)]} = \frac{\sigma^2}{\max\,[S(f)]}$$

where max $[S(f)]$ is the maximum of the spectral density function. This is identical with the equivalent noise bandwidth (the width of a rectangular filter passing the same spectral power as the process). The symmetrical measure of duration τ, is then:

$$\tau = \frac{\int_0^T x^2(t)dt}{\max\,[X^2(t)]} = \frac{T\sigma^2}{\max\,[X^2(t)]}$$

With the latter definition, to avoid the dependence on epoch length for non-time limited processes, it is desirable to introduce the concept of characteristic duration, D, as:

$$D = \frac{\tau}{T} = \frac{\sigma^2}{\max\,[X^2(t)]}$$

II. Behavioral Aspects of B vs. τ

A. Deterministic Functions

For nearly all families of simple isolated waveforms, the B τ product is a constant, thus the B vs. τ curve is a hyperbola as a function of the parameter defining different family members.

Some examples:

(a) $X(t) = e^{-a^2 t^2}$

$\tau = \frac{1}{2}\sqrt{\frac{\pi}{2}}$, $B = \frac{a}{2\sqrt{2\pi}}$, $B\tau = \frac{1}{4}$

(b) $X(t) = \frac{1}{a}$, $-\frac{a}{2\pi} \leq t \leq \frac{a}{2\pi}$

$= 0$, $|t| > \frac{a}{2\pi}$

$\tau = \frac{a}{\pi}$, $B = a\pi$, $B\tau = 1$

(c) $X(t) = \sin 2\pi ft$, $-\frac{a}{2} \geq t \geq \frac{a}{2}$

$= 0$, $|t| > \frac{a}{2\pi}$

If af is any integer,

$\tau = \frac{a}{2}$, $B = \frac{1}{a}$, $B\tau = \frac{1}{2}$

(d) $X(t) = e^{-2|a|t}$, $t \geq 0$

$= 0$, $t < 0$

$\tau = \frac{1}{a}$, $B = \pi a$, $B\tau = \frac{\pi}{2}$

B. Gaussian Processes:

If EEG sleep waves were the result of a summation of random neuronal firings "filtered" by the instrumentation system or by the brain itself, the EEG would be modeled by a narrow-band stationary Gaussian process (4) -- at least over moderate epoch lengths. For these processes, the characteristic duration is a (stochastic) function of bandwidth and epoch length whose expected value decreases as a function of the degrees of freedom (the equivalent number of independent samples) in the record. The degrees of freedom, n, in a finite sample of length, T, from a Gaussian process of bandwidth, B, is approximately $n = 2BT - 2/3$ (1) .

The expected Gaussian curve was computed by numerical integration and is plotted in Figure 2. For moderate degrees of freedom, the characteristic duration varies slowly around a value of 0.1.

RESULTS

Before presenting results obtained during sleep studies with implanted chimpanzee subjects, it is possible to diagram the relations between various wave patterns and their place in the stability diagram. Figure 2 demonstrates the various patterns for a selection of deterministic and random signals. The wave forms have been placed in the approximate position of their coordinates on the stability diagram. The minimum duration occurs with a single sharp spike.

Minimum bandwidth occurs with a sinusoid, maximum bandwidth with a spike or white noise. Usually, frequency modulation of a signal increases its bandwidth; amplitude modulation decreases its duration and increases its bandwidth. This can be seen in Figure 2 when the sinesoidal wave is compared to the FM modulation and the AM modulation.

The relation of typical EEG patterns to each other in stability are diagrammed in Figure 3, again, the wave forms approximate the actual coordinates. The data shown illustrate the extremes of patterns found in a single night's recording from a sleeping chimpanzee. Spectral analysis of these patterns did not reveal significant peaks since most of the power was in the lower frequencies although, it was possible to see local peaks. While it is possible to discriminate amongst adjacent patterns in the figure, they are of the type that visual examination would not separate in the context of a total EEG record. Thus, this pattern analysis reveals subtle shifts in rhythmic behavior of the record. It is possible, when using just coordinate points, to plot the differing segments of one night for a given placement against those records from differing placements. EEG records were visually analysed and different stages of sleep determined. These stages were then analysed by the computer and plotted on the stability diagram in terms of their respective bandwidths and durations. The results of this analysis can be seen in Figure 4 where the letters represent a coding of the clinically determined sleep stages and the cross hatchings the electrode placements.

Paradoxical or dream sleep, without consideration of its depth, appears close to the awake state in the mesencephalic reticular formation and entorhinal cortex on the basis of these stability parameters. By contrast, there are substantial differences between awake and paradoxical records from the parieto-occipital cortex (P.O.). However, a great similiarity in stability exists between paradoxical and drowsy stages for the parieto-occipital cortex. Both the entorhinal and parieto-cortex leads show close groupings for all types of slow waves while the mesencephalic reticular formation is somewhat spread. Note that the observed stability relationships do not tend to cluster about the expected Gaussian relationship, further evidence against the hypothesis of linear summation of neuronal spikes for the generation of EEG waves.

DISCUSSION

Systematic presentation of data, for either experimental or clinical purposes, requires a substantial degree of consistency. The stage at which the human observer enters into the interpretation of this data is usually where the greatest inconsistency also appears. At the same time, it is necessary to acknowledge that "clinical judgement is of vital importance, not only for patients but also in experimental situations. It would seem that the EEG is a prime example of this type of problem. In resolution of this difficulty, it becomes obvious that, the optimal system would be one which can present EEG data in the most concise and precise form, so that only clinical judgement is required and not interpretation of the form of the data. Recognition of this requirement is evidenced by the long history of proposed automatic systems (3,8). Unfortunately, this history also implies that for a variety of reasons, none of the systems have been very effective. The results presented above suggest that a critical failing of such systems has been their inability to discern and comprehensively consider those aspects of the pattern properties of the data to the extent used by electroencephalographers in reading records. This is not to imply that stability is the only factor utilized by an electroencephalographer. Work is currently underway to combine the bandwidth-duration type of information with a computer derived frequency amplitude measure. Presumably, by observing bandwidth,mean frequency, duration,and amplitude, one might proceed to a more accurate pattern discrimination approximating the clinician. Additionally, this technique may be applicable to derived EEG parameters such as the average of the evoked response.

At the present time, the bandwidth-duration measure as well as the proposed frequency-amplitude measure are derived in a fashion amenable to analysis with the large general purpose digital computer. However, these measures (or equivalents) could be obtained through analog devices, attached to normal EEG machines, and involving reasonable engineering requirements.

This general approach would seem to open wide areas for investigation in clinical and experimental neurophysiology and psychophysiology. It is suggested that this or a similar approach has the potential for fulfilling the early expectations and promise of the EEG. Furthermore, techniques to differentiate subtle states of consciousness in stress and other waking states seem necessary for further advances in our knowledge of human function. It is felt the first step in this direction has been made by demonstrating the subtle differences perceptible, after analysis, during normal sleep of the chimpanzee. Further support for this technique has been given by some preliminary stability analysis of drug effects on an EEG record of a psychotic patient by Dr. M. Fink. These early results showed promise of quantifying subtle EEG changes due to drugs.[3]

[3] We wish to express our thanks to Dr. Fink for kindly permitting us to review his preliminary results demonstrating the utilization of this concept.

SUMMARY

The concept of stability of an EEG tracing is introduced as replicating one of the major factors utilized in the clinical evaluation of EEG records. The mathematical formulae for defining stability and the theoretical behavior of deterministic and random processes are presented.

A stability diagram is shown giving typical distributions for bandwidth-duration relationships during an implanted chimpanzee sleep record.

A stability diagram is shown for a group of electrode placements (parieto-occipital cortex, entorhinal cortex and mesencephalic reticular formation) demonstrating separations of EEG patterns based, initially, on observed clinical categories.

The importance and utility of this approach for discriminating subtle changes in the EEG not consistently visible to the electroencephalographer, are discussed.

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Figure 1-A

Spectral Analysis from implanted bipolar electrodes in the mesencephalic reticular formation of the chimpanzee during three different states of consciousness, Awake, Deep, and Paradoxical Sleep.

Figure 1-B

Sample EEG tracings from the mesencephalic reticular formation during different states of consciousness.

Figure 2

Distribution of known signals when bandwidth is plotted versus characteristic duration.

Figure 3

Distribution of EEG tracings, during one night of sleep, plotted as bandwidth (B) versus duration (D). Coordinates for each tracing are directly above the respective tracing. Records are from the mesencephalic reticular formation (MBRF), the entorhinal cortex (ENT. CX.), and the Hippocampus (L. HIPP).

Figure 4

Plots of coordinates taken from visually evaluated EEG states, Awake (A), Drowsy (D), Waking (W), Paradoxical Sleep (P), Slow Wave sleep with more or less spindle activity (SL, SP, SS). Cross hatchings represent different electrode placements. P-O CORTEX is a parieto-occipital skull screw, ENT. CORTEX is a deep electrode in the entorhinal cortex, and MBRF is a deep electrode in the mesencephalic reticular formation.